

Learning Competition in Robot Soccer Game based on an Adapted Neuro-Fuzzy Inference System

Li Shi, *Student Member, IEEE*, Chen Jiang, Ye Zhen, Sun Zengqi, *Senior Member, IEEE*

Department of Computer Science The State Key Lab of Intelligent Technology & Systems
Tsinghua University, Beijing 100084, P.R.CHINA
Email: {lishi, yz} @s100e.cs.tsinghua.edu.cn, szq-dcs@mail.tsinghua.edu.cn

Abstract-RoboCup (Robot World Cup Tournament) is a worldwide popular research domain in recent years. The main dealing of it includes complex system behavior of multiple autonomous agents. Because of the complexity of system, how to describe cooperation and competition between agents becomes a great challenge in RoboCup Simulation Game. On one hand, the rich experience of human soccer player is of great service to the robot players. On the other hand, the difference between simulation game and real game make it a must to fit the transcendental knowledge into the new environment. Commonly used reinforcement learning is weak in utilizing transcendental knowledge, thus is limited in complex Multi-agent System (MAS) learning problems. This thesis puts forward a supervised learning method on the basis of Adapted Neuro-Fuzzy Inference System (ANFIS) to mapping the competition among the robots. This method can build an ANFIS according to experts' knowledge, and with data obtained in the simulation environment; it is able to adjust parameters of the system's antecedents and consequents in a self-adapt way. So it can establish a correct map to describe the competition among the robots.

We use this method to describe the antagonization between the shooter and goalie, and successfully apply it in the RoboCup Simulation Game to build the champion team in RoboCup 2000 of China.

Keywords RoboCup, MAS, ANFIS, Machine Learning

I. INTRODUCTION

In recent years, research in MAS and distributed AI has become a main stream of AI research. With human society as its reference, MAS focus on collective intelligent behavior[1]. It has been applied in software agents, intelligent manufacturing systems, electronic commerce[2], etc. RoboCup, Robot World Cup Tournament[3], is a typical MAS. By the study of robot football game, people learn how to cooperate and coordinate multiple robots. RoboCup Simulation Game is a standard simulation game defined by RoboCup League. It is marked by its dynamic environment, the co-existence of cooperation and competition among several agents, limited communication bandwidth, and the noisy environment, which make it a good test-bed for MAS research and application.

Multi-Layer feedforward neural network[4] and Reinforcement Learning[5] are usually used by the teams competing in RoboCup to depict the complex relation among the robots. Both methods are good in some area and have proved themselves in RoboCup. Yet they all have shortcomings.

For most application, though simple as the environment may be, defining the entire behavior of the system at designation is impracticable, considering that the environment is dynamic. Learning and adapting ability is important to the agents. There are many classification of learning. If we classify learning according to learning feedback, we get Supervised Learning, Reinforcement Learning (RL), Unsupervised Learning[6], among which Reinforcement Learning get more attention because of its online capability and the ability to learn optimal policy in an entirely unknown environment[1]. However, Reinforcement Learning has its weak points. First trial-and-error method is not suitable for expressing rules, and thus is weak in utilizing transcendental knowledge. Second, RL Algorithm for MAS is developed from typical RL Algorithm, which is for a single agent, and is not competent in dealing complex MAS learning problem[2]. Multi-Layer feedforward neural network is poor in expressing rule knowledge.

In Robot Soccer Game, the rich experience of human soccer players is of great significance to the designation of robot players. In order to make full use of this transcendental knowledge, we consider Fuzzy Inference System (FIS). As a powerful tool handling greatly nonlinear and nondeterministic system, FIS has been successfully applied in many decision-making and control area[7]. Combined with a neural network to adapt fuzzy rules of the system, FIS can achieve the ability of self-learning and adapting. This combination can yield pretty good results. We design a supervised ANFIS learning method to build the mapping of the complex relations of robots.

First we divide soccer court, set up corresponding membership function for each division. Then we constitute fuzzy rules according to the worthy experience of excellent human soccer players, namely transcendental knowledge. Whereafter we gather data from simulation games, which are used to adjust the membership of the system to be suitable for the game as expected.

II. COMPETITION OF MULTI-ROBOT USING ANFIS

In a complex system with multiple autonomous robots, robots try to gain their own interest through various cooperation and competition. Relation among robots can be viewed as a map from the state of the robot to $[0, 1]$. This mapping represents the likelihood of selecting some action to cooperate and compete with other robots in the current state of the robot. This mapping provides necessary reference for the robot's top-level decision. This thesis only deals with the competition between multiple robots.

A. Basic definition and hypothesis

We make the following definition and hypothesis for RoboCup Simulation Game.

Suppose $A = \{a_1, a_2, \dots, a_n\}, n \in N$, representing a set of n agents. S denotes the environment of A . Let $\Psi : \{\phi_1, \phi_2, \dots, \phi_o\}, o \in N$ denote the action set of A .

Defining 1: MAS $\Phi : \Phi = A + S$.

Suppose A is running in S . S is static but noisy. S randomly brings noise to each Agent $a_i \in A$, influence the precision of sensory information and interfere the performance of action[8].

We take into account the competition between a_i and another agent a_{-i} (here a_{-i} denote all agents in A except a_i).

Definition 2: A union represents a group of cooperating agents.

Suppose there are $k(k \leq n-1)$ unions among a_{-i} . Each single agent who does not cooperate with others becomes a union itself. The numbers of agents in the unions form the set $C : \{c_1, c_2, \dots, c_k\}$. The sum of elements of C is equal to $n-1$. The structure of a_i is demonstrate in Figure 1, there are k ANFIS' and every ANFIS denotes the complex relations of competition between a_i and one of the union. The structure of ANFIS will be introduced in detail in the next section.

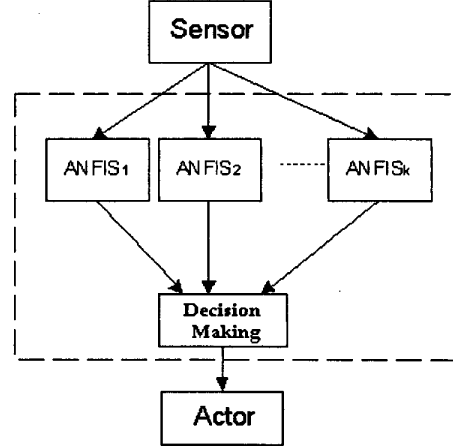


Figure. 1. Top-level decision-making structure of a_i

B. Adapted Neuro-Fuzzy Inference System

We design a multiple-input single-output ANFIS. The input vectors including the state of a_i itself and the action that a_i is to take, and also the states of agents in the union $j, (1 \leq j \leq n-1)$. The output of the system shows the likelihood of success of the action a_i selects when it confronts the union j . As shown it Figure 1, there are k such ANFIS' representing k unions. The output of the ANFIS provides reference for the decision-makers.

Let input vector be $X = [x^i \ x_{\phi_p}^i \ x_1^j \ \dots \ x_{c_j}^j]^T$. x^i denotes the current state of a_i , $x_{\phi_p}^i, (1 \leq p \leq o)$

denotes the action of a_i , c_j vectors after represent the states of the agents of the union j . Every elements of the vectors are fuzzy language elements. Suppose that there are totally Ω elements. Thus there are Ω inputs of all ANFISes. ξ_i is the set of the fuzzy language elements of the i th input with ξ_i elements.

$A_q^h (h=1,2,\dots,\xi_q; q=1,2,\dots,\Omega)$ denotes the h th elements of the q th inputs. The corresponding membership function is $\mu_{A_q^h}(x) (h=1,2,\dots,\xi_q; q=1,2,\dots,\Omega)$. We choose Gauss

Function as the membership function: $\mu = e^{-\frac{(x-c)^2}{\sigma^2}}$, where c, σ represent the center and the width of the membership function respectively. In order to apply neural network to adjust the system, we choose TS model put forward by Takagi and Sugeno. The consequents of fuzzy rules are expressed as linear combination of inputs, namely

R_m : If x_1 is A_1^m and x_2 is $A_2^m \dots$ and x_n is A_n^m , then

$$y_m = p_{m0} + p_{m1}x_1 + \cdots + p_{mn}x_n.$$

Where $m \in N, m \leq \prod_{i=1}^{\Omega} \xi_i$.

According the model given above, we can design a fuzzy neural network system as shown in Figure 2.

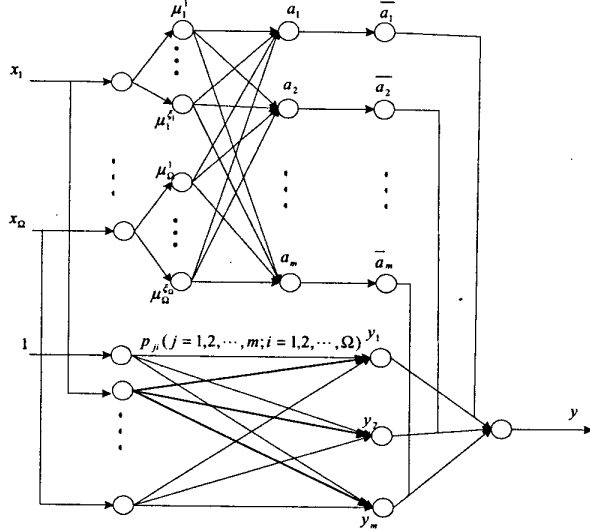


Figure.2. Structure of ANFIS'

Shown as Figure 2, the top half is antecedent network matching the antecedents of fuzzy rules. The lower half is consequent network producing the consequents of fuzzy rules.

1) Antecedent network

The antecedent network comprise of four layers. The first layer is input layer and is directly connected with the elements of input x_i . Each node of the second layer represents a language variable. It is used to compute the membership function μ_i^j of how each language element belong to each language variable set.

$$\mu_i^j \triangleq \mu_{A_i^j}(x_i) \quad i = 1, 2, \dots, \Omega; j = 1, 2, \dots, \xi_i$$

Ω is the dimension of inputs, ξ_i is the number of fuzzy divisions of x_i . There are $m(m \leq \prod_{i=1}^{\Omega} \xi_i)$ nodes in layer 3,

which represents a fuzzy rule matching the antecedents of fuzzy rules. It computes the applicability of each fuzzy rule $a_j = \min\{\mu_1, \mu_2, \dots, \mu_{\Omega}\}$.

Layer 4 possesses the same number of nodes with Layer 3, say, $N_4 = N_3 = m$. It implements aggregation computation,

$$\bar{a}_j = \frac{a_j}{\sum_{i=1}^m a_i} \quad j = 1, 2, \dots, m.$$

2) Consequent network

The first node of the input layer is a biased node with constant input $x_0 = 1$. The function of Layer 5 is to compute the consequents of fuzzy rules,

$$y_j = p_{j0} + p_{j1}x_1 + \cdots + p_{jn}x_n = \sum_{k=0}^{\Omega} p_{jk}x_k,$$

where $j = 1, 2, \dots, m; m \leq \prod_{i=1}^{\Omega} \xi_i$.

The layer 6 calculates the output of system,

$$y = \sum_{j=1}^m \bar{a}_j y_j$$

It is obvious that y is the weighted sum of the rule consequents. The weights are just the aggregated applicability of the fuzzy rules. They are the connecting weights of the effect that the antecedent network imposes on the third layer of the consequent network.

C. Designation of learning algorithm

Every ANFIS need be trained alone, because the different ANFIS expresses different relations among robots. Every ANFIS need the different training data. Because the number of divisions of each input variables are predefined, the parameters to be adjusted through learning are mostly the connecting weights of the consequent network $p_{ji} (j = 1, 2, \dots, m; i = 0, 1, \dots, \Omega;)$ and the centers c_{ij} and widths $\sigma_{ij} (i = 1, 2, \dots, m; j = 1, 2, \dots, \xi_i)$ of the membership function in the nodes of Layer 2 of the antecedent network. The error function is chosen as:

$$E = \frac{1}{2}(y_d - y)^2$$

where y_d and y denote the expected output and the real

output respectively. The learning algorithm of parameters p_{ji} is given below.

$$\frac{\partial E}{\partial p_{ji}} = \frac{\partial E}{\partial y} \frac{\partial y}{\partial y_j} \frac{\partial y_j}{\partial p_{ji}} = -(y_d - y) \bar{a}_j x_i$$

$$p_{ji}(l+1) = p_{ji}(l) - \beta \frac{\partial E}{\partial p_{ji}} = p_{ji}(l) + \beta(y_d - y) \bar{a}_j x_i$$

where $j = 1, 2, \dots, m; i = 0, 1, \dots, \Omega$.

Following is the discussion of the learning problem of the centers c_{ij} and the widths σ_{ij} . Fix p_{ji} , Figure 2 can be simplified to Figure 3.

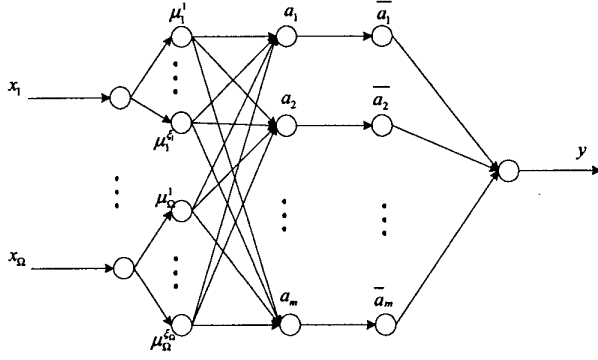


Figure 3 the structure after simplified

The consequents of the rules become connecting weights of the last layer in the simplified structure. This simplified structure is identical to the standard fuzzy neural network. Let the weights of the last layer $y_j = w_j$, the above results are also applicable,

$$\begin{aligned} \delta^{(5)} &= y_d - y \\ \delta_j^{(4)} &= \delta^{(5)} y_j, j = 1, 2, \dots, m \\ \delta_j^{(3)} &= \frac{\delta_j^{(4)} \sum_{i=1}^m \alpha_i}{\left(\sum_{i=1}^m \alpha_i \right)^2} \quad j = 1, 2, \dots, m \\ \delta_{ij}^{(2)} &= \sum_{k=1}^m \delta_k^{(3)} S_{ij} e^{-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}} \quad j = 1, 2, \dots, m \end{aligned}$$

where if we use minimization operation for and operation, and μ_i^j is the minimum of the inputs k rule nodes, $S_{ij} = 1$.

Otherwise, $S_{ij} = 0$. Thus we get

$$\begin{aligned} \frac{\partial E}{\partial c_{ij}} &= -\delta_{ij}^{(2)} \frac{2(x_i - c_{ij})}{\sigma_{ij}^2} \\ \frac{\partial E}{\partial \sigma_{ij}} &= -\delta_{ij}^{(2)} \frac{2(x_i - c_{ij})^2}{\sigma_{ij}^3} \\ c_{ij}(k+1) &= c_{ij}(k) - \beta \frac{\partial E}{\partial c_{ij}} \\ \sigma_{ij}(k+1) &= \sigma_{ij}(k) - \beta \frac{\partial E}{\partial \sigma_{ij}} \end{aligned}$$

where $\beta > 0$ is the learning rate,

$$j = 1, 2, \dots, m; i = 0, 1, \dots, \Omega.$$

The learning algorithm adapts the consequent connecting weights of FIS and the morphs of antecedent membership function to produce a more precise output. Furthermore,

neural-network based structure proves great resistance to the interference of the environment S .

III. LEARNING SHOOT WITH ANFIS

Shoot is an important skill in soccer game. So we choose shoot to validate the effect of ANFIS. In the view of MAS, shoot is competition among several agents. It is not difficult to perform a shoot, but how successful the shoot will be proves to be a great trouble to evaluate. The decision maker decides whether or not to perform this action according to the possibility of a goal. The success rate of shoots is related to the states of other agents, such as the position of our shooter, the positions of the opponent defenders, the defending ability of the opponent defenders, the position of the opponent goalie, and its defending ability, etc. Peter Stone[4] realizes the antagonization between a shooter and a goalie using multi-layer feedforward neuro-network. However multi-layer feedforward neuro-network is helpless if more robots are took into account. As we present below, we implement the mapping in the multi-robot environment with ANFIS.

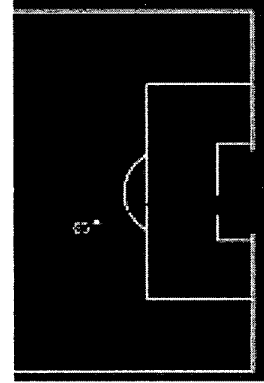


Figure.4. Data Collection.(Yellow is the shooter, Red is the defender and the Purple is the goalie)

First, we examine the instance when there are just a goalie and one defender. Figure 4 denotes the play. Since the goalie and the defender pursue the same goal, namely they cooperate, we classify them in the same union. So the structure of a_i has only one ANFIS, which represents the competition between a_i and the union. There are 7 inputs of the system: X, Y coordinates of the shooter, the expected shoot angle, X, Y coordinates of the goalie and the defender. They are fuzzily divided as [near far], [left right], [left right], [near far], [left right], [near far], [left right] respectively. Altogether there are at most 128 fuzzy rules. On occasions with even more rules, we can employ fuzzy clustering algorithm to cut down the rules. We use Gauss function as the membership function. The learning algorithm modulates the shape of the curve by regulating the parameters of the function. The initial curves are shown in Figure 5. The output of the system is the success rate if the shooter shoots with the expected angle.

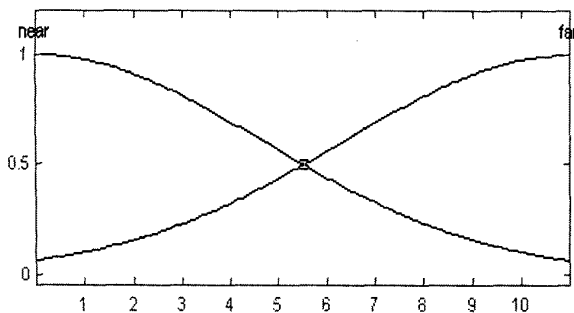


Figure.5. membership function of input

We construct certain situations in RoboCup simulation environment to train the shooter. We select CMUnited99 (the 99 RoboCup World Champion Team of Simulation League) as the opponent. We fuzzily partition the area near the goal, and randomly place the shooter, the defender and the goalie in the partitioned area. The shoot point is also randomly chosen in the range of the goal, and the shoot angle is calculated according to the position of the shooter and the shoot point. We try 10 shoots for each angle. The success rate of each shoot is computed as the goals divided by 10. We train the ANFIS with 5000 data obtained in the real competition between our shooter and CMUnited99 defender and goalie.

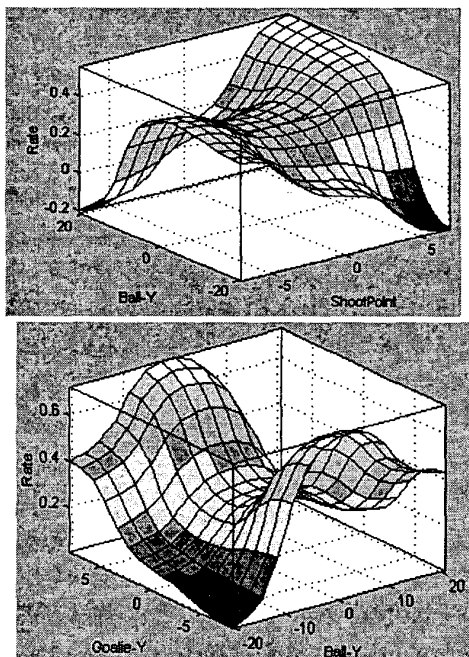


Figure. 6. The adjusted mapping between the shooter's position and the shoot angle (left-down) and the shooter's position and the goalie's position(right-up)

The trained ANFIS more precisely describes the relations between the shoot angle and the goalie's position and the shooter's position. We test the trained ANFIS with other 100 data. The average error of the system is 14%.

Because we choose the champion team as the opponent, the trained ANFIS may overrate the opponents. The real success rate may be higher than that when the shooter faces average defenders. But this doesn't cause real problems for application. Our shooter will be more conservative, but safer.

IV. CONCLUSION

This thesis presents an Adapted Neuro-Fuzzy Inference System based method to describe the competition between multiple robots. And the author successfully applied it in the RoboCup Simulation environment. The introduction of FIS to MAS algorithm will make full use of the ability of FIS to deal with greatly nonlinear and nondeterministic system. The application of neuro-network to adjust the parameters of FIS (ANFIS) avails itself of the ability to describe the system more exactly.

REFERENCES

- [1] Gerhard Weiss, *Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence*, the MIT Press, 1999.
- [2] Eugénio Oliveira, Klaus Fischer, Olgastepankova, "Multi-agent systems: which research for which applications", *Robotics and Autonomous Systems* 27 (1999) 91-106, Elsevier Science, 1999.
- [3] Hiroki Kitano, Minoru Asada, Yasuo Kuniyoshi, Itsuki Noda, Eiichi Osawa, Hitoshi Matsubara, "RoboCup: A Challenge Problem for AI and Robotics", *RoboCup-97: Robot Soccer World Cup I*, 1-19, Springer, 1998.
- [4] Peter Stone, "Layered Learning in Multi-agent System", PHD dissertation, school of computer science, Carnegie Mellon University, 1998.
- [5] Kostas Kostiadis, Huosheng Hu, "Reinforcement Learning and Co-operation in a Simulated Multi-agent System", *Proceedings of the 1999 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 990-995, 1999.
- [6] Gerhard Weiss, "Distributed artificial intelligence meets machine learning : learning in multi-agent environments", Springer, Berlin, 1997.
- [7] Yan, X.W., Deng, Z.D., Sun, Z.Q., "Fuzzy advantage learning", *IEEE International Conference on Fuzzy Systems* 2 May 7-May 10 2000, p 865-870, 2000.
- [8] Itsuki Noda et al, "Soccer Server Manual", RoboCup Federation. <http://www.robocup.org>.
- [9] Chin-Teng Lin, Chia-Feng Juang, Chung-Ping Li, "Water bath temperature control with a neural fuzzy inference network", *Fuzzy sets and Systems* 111 (2000) 285-306, ELSEVIER Science.
- [10] Jorg P. Muller, "The Design of Intelligent Agent", Springer, 1996.
- [11] Hans-Dieter Burkhard, Markus Hannebauer, Jan Wendler, "AT Humboldt - Development, Practice and Theory", *RoboCup-97: Robot Soccer World Cup I*, 1-19, Springer, 1998.
- [12] Jukka Rieki, "Reactive task execution of a mobile robot", PHD dissertation, Infotech Oulu and Department of Electrical Engineering, OULU, 1998.
- [13] Hiroki Kitano, *RoboCup-98: Robot Soccer World Cup II*, Springer, 1998.